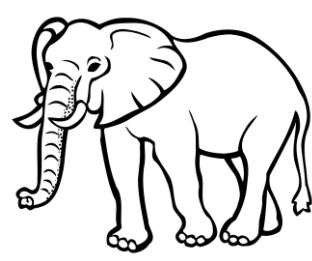


"Next-Generation Habitat Suitability Modeling: From Ensemble SDMs to Automated Machine Learning for Elephants"



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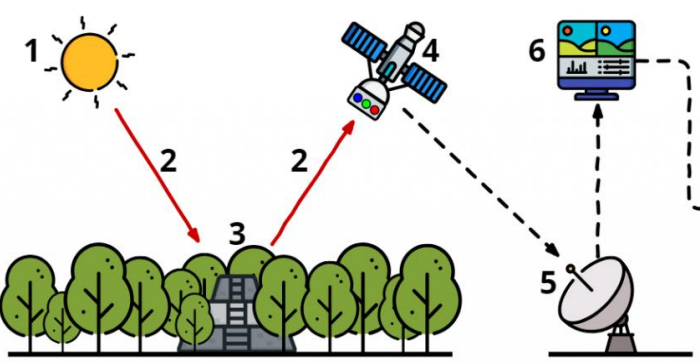
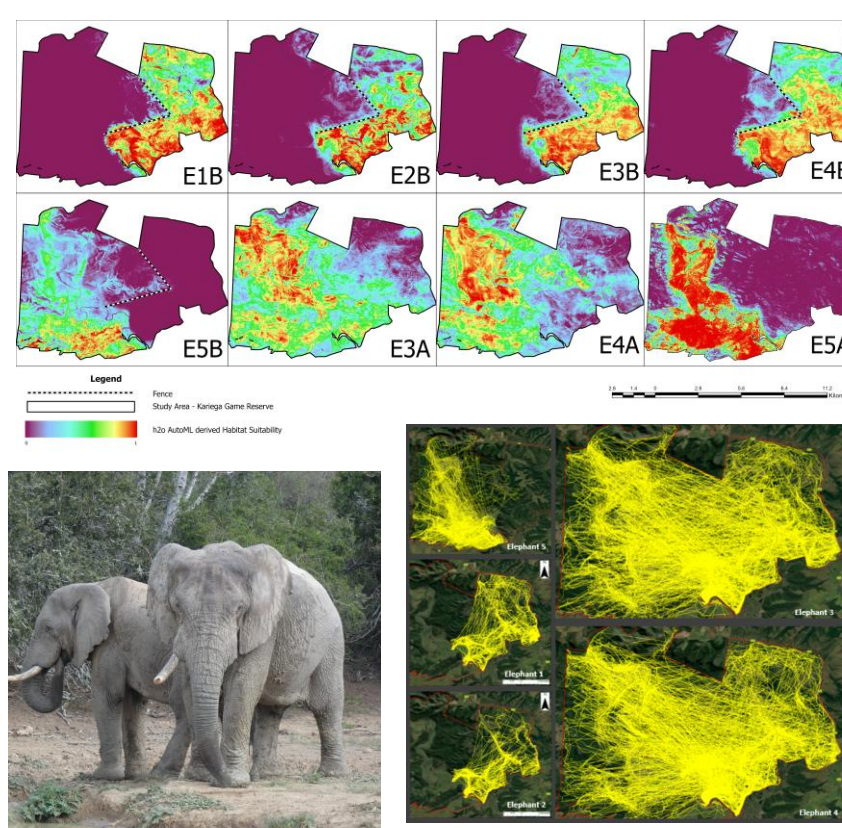
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Abstract

Automated machine learning (AutoML) enhances modeling ecological trade-offs of fencing for keystone species by analyzing habitat changes after fence removal. In Kariega Game Reserve, telemetry data from six elephants and environmental variables were used to compare stacked ensemble species distribution models with the h2o AutoML framework.

AutoML outperformed traditional models in accuracy (AUC \approx 0.90 vs. 0.85) and better detailed post-fence habitat expansion. The study highlights the potential of scalable AutoML in spatial ecology for conservation, providing a robust, benchmarked framework for future habitat suitability prediction under climate scenarios. This approach offers precise, scalable insights crucial for keystone species management and landscape connectivity planning.



Introduction

1. The Challenge: Elephant Conservation vs. Habitat Fragmentation

African elephants are ecosystem engineers that shape landscapes and support biodiversity, yet populations have declined by 77% over 50 years. Wildlife fences reduce human-wildlife conflict but fragment habitats, limiting elephant movement and access to resources. Kariega Game Reserve removed internal fences (Sept 2022 & Jan 2024), merging Kariega West (2,792 ha, 55 elephants) and Harvestvale (4,369 ha, 20 elephants) into one 8,192 ha landscape

2. The Gap: Traditional Models vs. Modern Machine Learning

Species Distribution Models (SDMs) predict habitat suitability but require manual tuning and struggle with reproducibility. AutoML automates model selection and optimization, potentially offering faster, more accurate predictions. This study benchmarks h2o AutoML against traditional ensemble SDMs using GPS data from six collared elephants before and after fence removal.

Research Question: How do h2o AutoML and traditional ensemble SDMs differ in predicting elephant habitat suitability changes after fence removal, and what are the conservation implications of these methodological differences?

We hypothesize that AutoML offers a more encouraging outlook, with stronger gains and lasting impact, while SSDM tends to provide a more cautious, stability-focused perspective

Methodology

Step 1: Data Collection & GPS Tracking

- Six GPS-collared elephants tracked at 30-minute intervals (Aug 2022–Feb 2025): 127,717 locations spanning fence removal periods.

Step 2: Spatial Thinning with DBSCAN

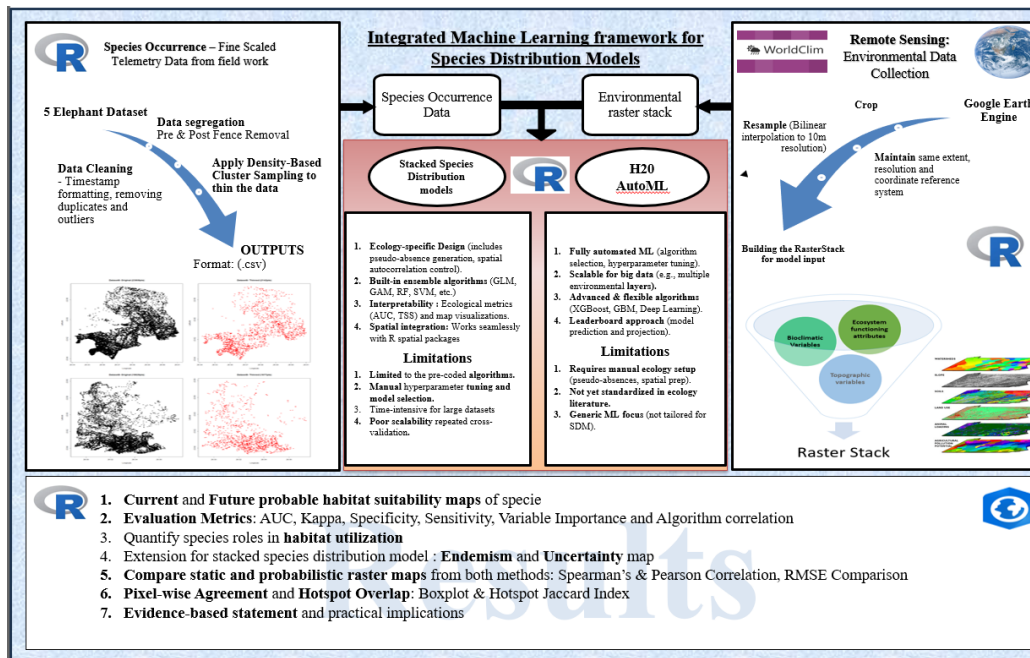
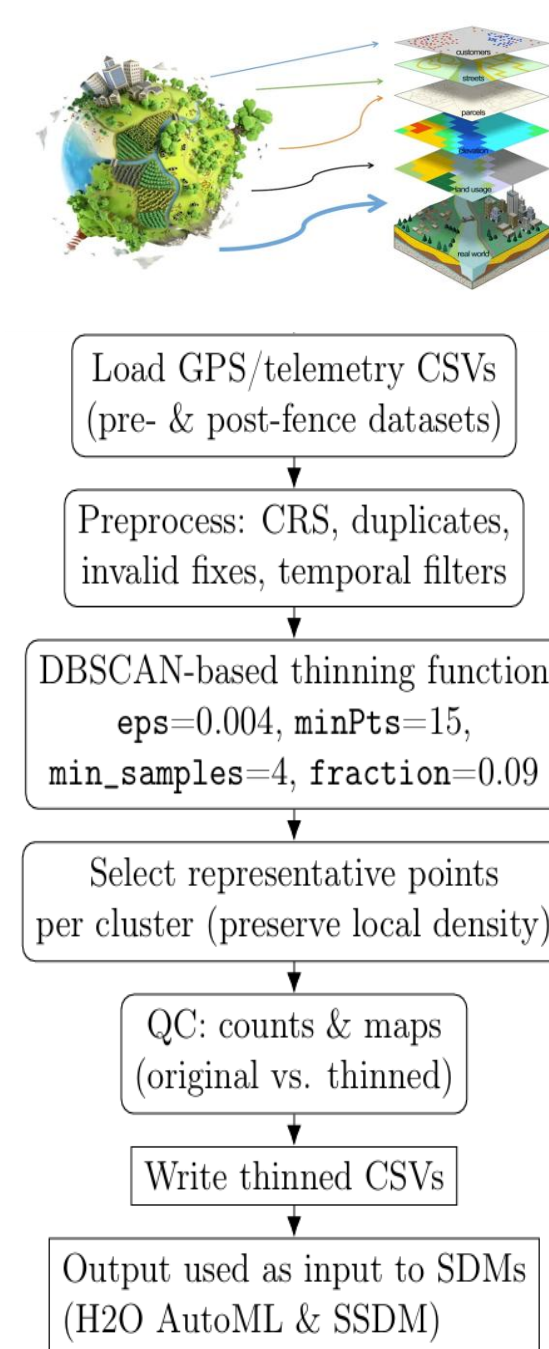
- DBSCAN spatial thinning (400m radius, 20% retention) reduced the dataset to 14,522 representative points while preserving spatial structure and reducing autocorrelation.

Step 3: Environmental Predictors Stack

- 26 environmental variables from Sentinel-2 (NDVI/EVI, 10m), SRTM ESA land cover, and 19 bioclimatic variables, 1km were compiled and filtered ($r > 0.8$) to reduce multicollinearity

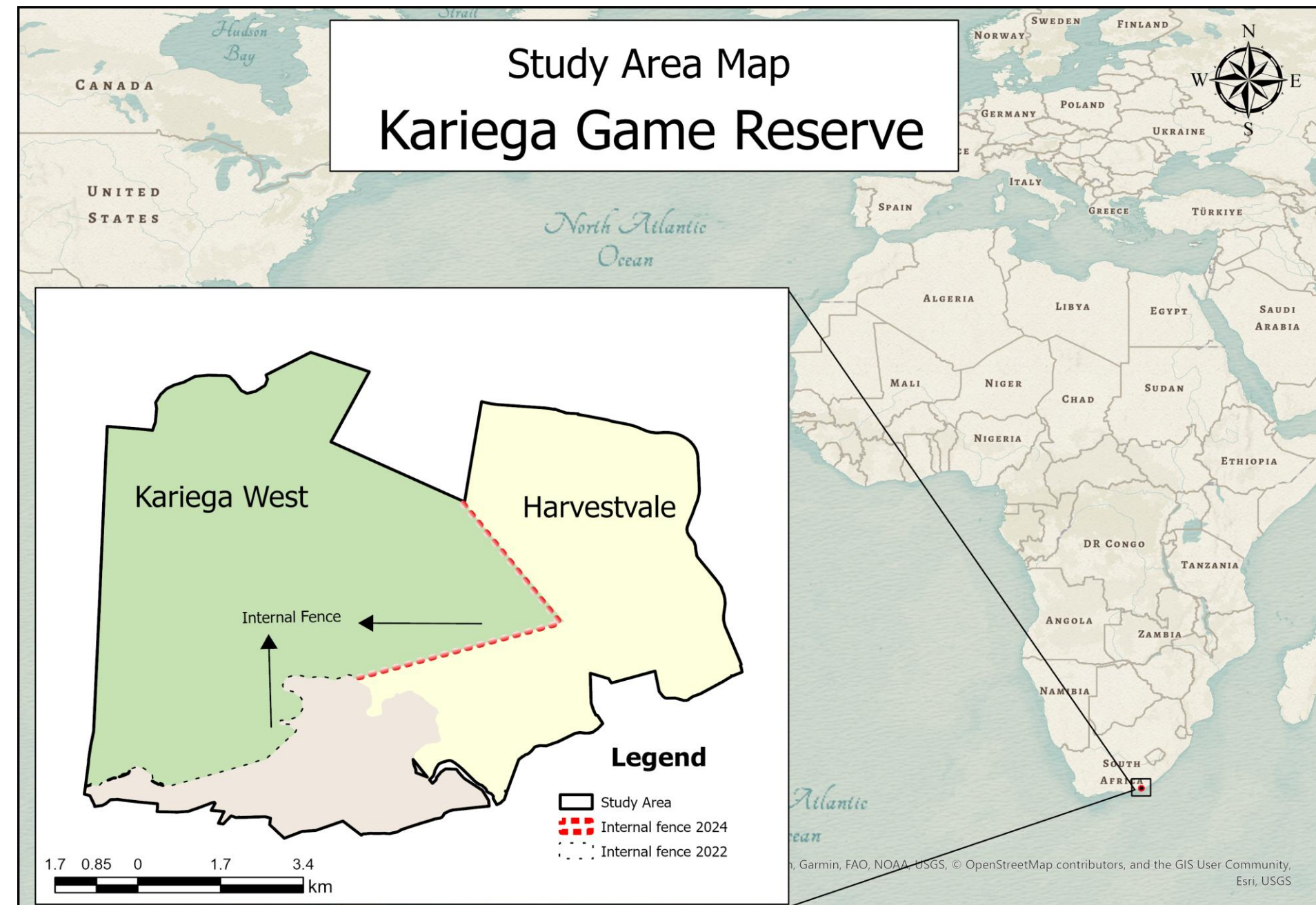
Step 4: Dual Modeling Framework Comparison

- Two modeling approaches: traditional SSDM (8 algorithms) and H2O AutoML (adaptive ensemble) were evaluated using AUC, spatial correlation, RMSE, and hotspot overlap (Jaccard Q75).



Study Context

Location: Kariega Game Reserve, Eastern Cape, South Africa
Intervention: Internal fence removal (Sept 2022 & Jan 2024)



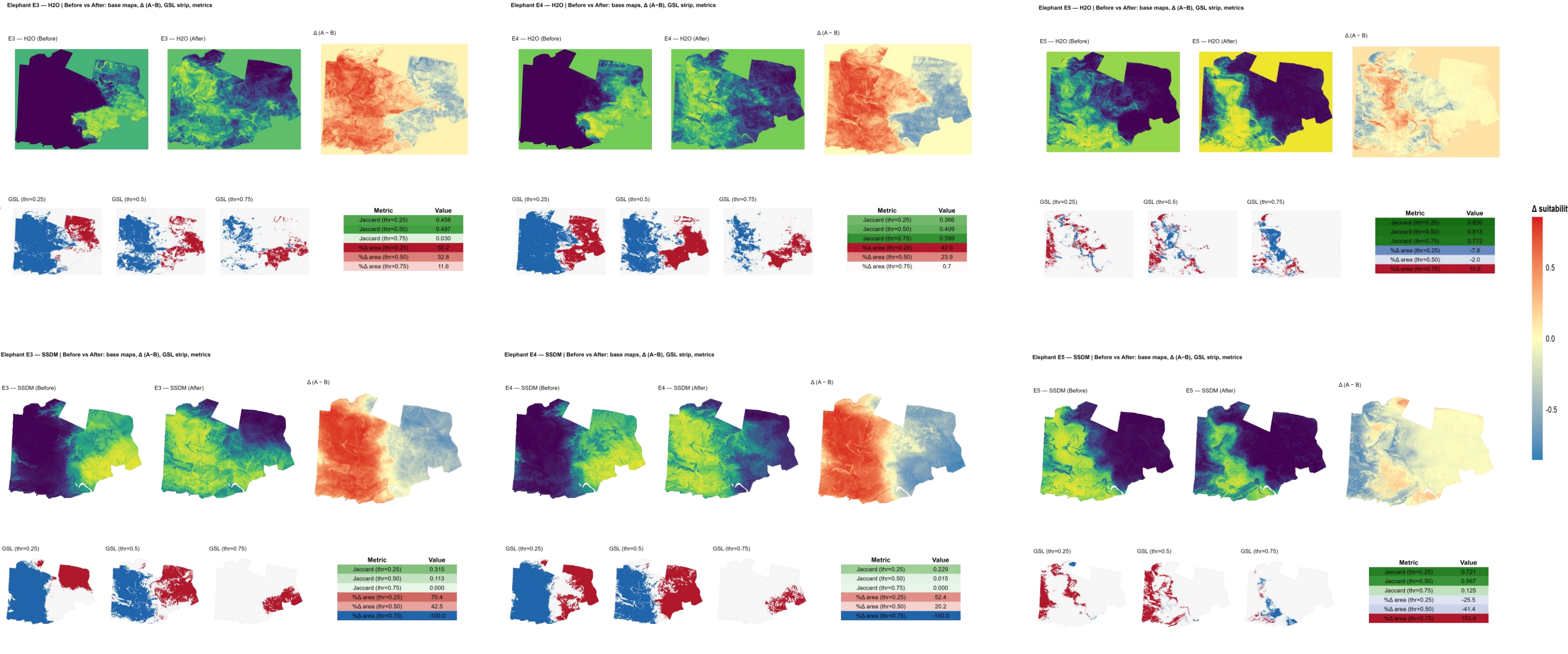
Results

h2o AutoML: Superior & Sensitive

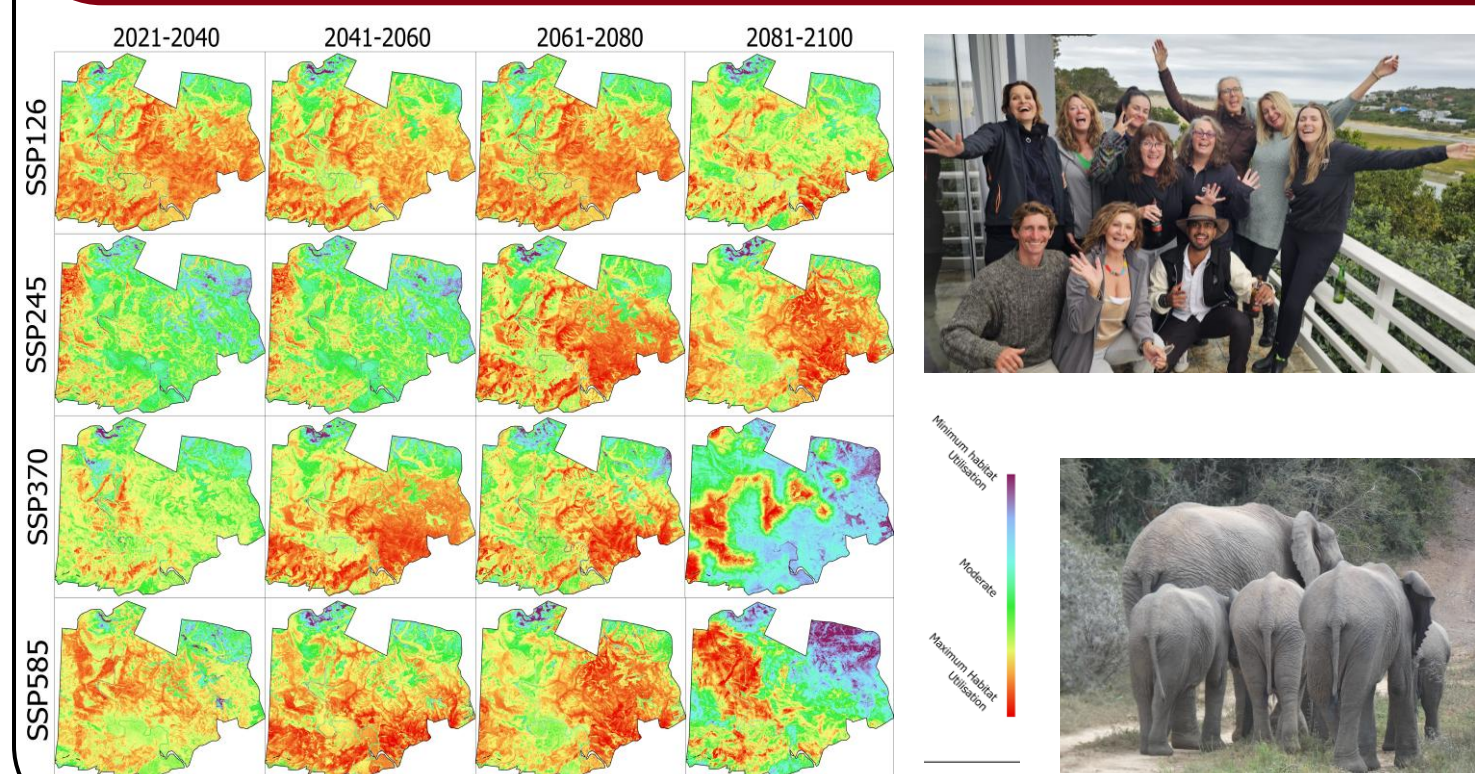
h2o AutoML achieved higher accuracy (AUC 0.90 vs. 0.85) and detected up to 35% habitat expansion post-fence removal with sharp spatial boundaries. This framework provides stronger predictive gains with maintained core areas, ideal for identifying restoration opportunities.

Traditional SSDM: Conservative & Stable

Traditional SSDM achieved solid performance (AUC 0.85) but predicted complete core habitat loss (~100%) at strict thresholds for E3 and E4. This stability-focused approach with smoother transitions serves as a conservative baseline for risk assessment.



Conclusion



h2o AutoML outperformed traditional SSDM with superior accuracy computational efficiency, and adaptive optimization per individual elephant, making it particularly valuable for species-specific conservation planning. Complete fence removal enabled substantial habitat expansion, with elephants rapidly exploiting newly accessible high-quality areas individual responses varied as experienced matriarchs (Bukela) showed pronounced expansion while others followed existing corridors (Beauty) or displayed exploratory behavior (Half-Moon). Despite high correlation, frameworks shared only 17–28% of core habitats, highlighting critical methodological uncertainty; **AutoML offers sensitive predictions with sharp boundaries while SSDM provides conservative baselines with temporal stability, and together they bracket the plausible uncertainty envelope for evidence-based management.** Future projections show stable habitat under low emissions (SSP1-2.6) but substantial loss under high emissions (SSP5-8.5) by 2100, emphasizing that current connectivity restoration is urgent as corridors established now may prove essential for enabling future climate-driven range shifts and maintaining population viability.

Future Directions

Integrate mechanistic models (RSFs/SSFs) with AutoML for behaviorally patterns

Incorporate multimodal data: acoustics, genetics, human-wildlife conflict records

Link habitat selection to carbon sequestration and ecosystem services

Scale to landscape, regional, and continental analyses for broader conservation impact

Share open-source workflows for reproducibility and collaborative advancement

And the Most important!

Interdisciplinary collaboration.

Discussion

1. AutoML vs. Traditional SSDM

Superior Performance: h2o AutoML outperformed SSDM with higher AUC (~0.90 vs. 0.85), lower RMSE, and sharper boundary delineation. AutoML adaptively optimizes model architecture per individual, capturing complex ecological discontinuities critical for conservation.

Computational Efficiency: Parallelized architecture reduced training time while maintaining accuracy practical for large-scale multispecies studies.

2. Fence Removal Impact

Habitat Expansion: Up to 35% habitat suitability increase post-fence removal, with individual variation:

- Bukela (E3):** Pronounced expansion into Harvestvale (experienced matriarch)
 - Half-Moon (E4):** Exploratory gain/loss patterns (initial post-barrier investigation)
 - Beauty (E5):** Modest corridor expansion (optimized selection)
- Vegetation Shift:** NDVI/EVI gained importance, indicating rapid exploitation of high-productivity forage in newly accessible areas.

3. Framework Uncertainty

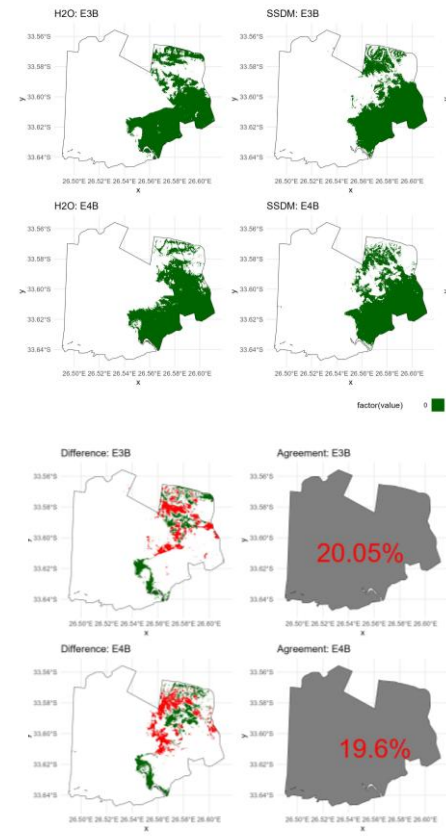
Limited Overlap: Only 17–28% hotspot agreement despite strong correlation, reflecting different algorithmic sensitivities to environmental gradients.

Conservation Value: AutoML provides sensitive predictions (sharp boundaries, larger gains); SSDM offers conservative baseline (temporal stability). Together they bracket uncertainty essential for high-stakes decisions.

Risk: Single-framework reliance may over- or underestimate critical habitat areas.

4. Climate Urgency

Future Projections predicts substantial loss by 2100. Connectivity restoration may enable future climate-driven range shifts restoration is urgent now.



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